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ABSTRACT

This paper explores various procedures of panel data in the estimation of causal models. The reported analyses are from the Monitoring the Future study, a nationwide questionnaire survey of 16,000 to 17,000 high school seniors conducted annually since 1975. First, the parameters of causal models are estimated in which the dependent variables are two reports on the overall quality of life. The exercise is then repeated using two measures of drug abuse as the dependent variables. Multiple regression analyses were performed and results are presented briefly in tabular form. Change scores offered a clear advantage over the use of static scores by reducing the potential for misspecified models. In general, the standard errors of estimates based on change scores are greater than those based on static scores. However, present results indicate that for reasonably large sample sizes, and for a wide range of stabilities of the true values and measurement errors in the predictor variables, the ratio of sampling errors for estimates based on change scores to those based on static scores is not excessively large. Panel data as estimates of dynamic causal models are also discussed. (PN)

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Comparison of Alternative Approaches to Causal Analysis with Panel Data

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Comparison of Alternative Approaches to Causal Analysis with Panel Data

Objectives

Panel data have often been regarded as the social scientist's answer to the experimental techniques available to natural and physical scientists. Unfortunately, panel data are not a panacea, and researchers are increasingly coming to recognize that drawing causal inferences from panel data, just as in the case of cross-sectional data, requires the imposition of some implicit or explicit causal model. Nevertheless, although panel data do not relieve us of the requirement of a causal model (including the imposition of some untestable assumptions), panel data do offer important advantages over cross-sectional data in the estimation of the parameters of such a causal model. In this paper our objective is to explore the usefulness of various procedures of panel data in the estimation of causal models. We focus here on the more familiar static models, but we have elsewhere employed similar procedures using panel data to estimate dynamic models as well (Rodgers and Bachman, 1985).

The particular relationship that we seek to explain is that between marital status and self-reported levels of happiness and satisfaction with life. We also examine briefly the relationship between marital status and use of alcohol and marijuana. Using data from national samples both of adults of all ages and of young people in the first few years following graduation from high school, we have found that married respondents report higher levels of satisfaction with their lives than do unmarried respondents. Several explanations can be posited to explain this relationship. Perhaps the first to come to mind is that marital status has a causal effect on subjective well-being. Several intervening variables might account for such an effect: for example, being married may be directly responsible for greater fulfillment of any number of psychological and biological needs, and the extent to which such needs are met may in turn have a causal influence on satisfaction.

The notion that marriage influences satisfaction is not, however, the only plausible interpretation of the relationship between marital status and life satisfaction. One

alternative is that the causal flow is in the reverse direction: those who are more satisfied with their lives are more likely to enter into, and remain in, the married status. Indeed, it is entirely possible that both causal mechanisms are at work. Nor have we by any means exhausted the list of possible interpretations of the simple relationship between two variables. Another possibility is that the relationship is entirely or partially spurious, reflecting not a causal influence of either variable on the other, but the influence of one or more other variables on both of these observed variables. For example, one could posit a personality characteristic which influences both the probability of marriage and the level of life satisfaction. Another interpretation is that measurement factors are responsible for the observed relationship. For example, unmarried respondents may differ from married respondents in being more willing to admit to problems and dissatisfactions.

In order to quantify the impact of one state on another, it is necessary to specify a causal model and to estimate the parameters of that model. Consider, for example, the relationship between marital status and reported life satisfaction. To represent the hypothesis that this relationship reflects the causal influence of marital status on satisfaction, we can write the following expression:

$$Y_i = \sum_{j=1}^{J} \beta_j D_{ij} + \epsilon_i \quad . \tag{1}$$

The independent variable, marital status, is simply a set of categories and so is represented by a set of dummy variables, D_{ij}, each of which is equal to 1 if individual i is in marital status j, or 0 if that individual is in any other marital status. For individuals in marital status j, the model specifies that their expected satisfaction is a particular value represented by the parameter β_j. This parameter can be estimated very simply by finding the average satisfaction level of the individuals in the sample who are in status j. ϵ_i, then, is the deviation of the satisfaction reported by individual i from the average for all persons in his or her marital status.

More generally, the model for differences in satisfaction between respondents in different marital statuses can be expanded to take account of other characteristics of the respondents thought to influence levels of satisfaction:

$$Y_i = \sum_{j=1}^{J} \beta_j D_{ij} + \underline{X}_i \underline{\gamma} + \epsilon_i \ . \qquad (2)$$

where $\underline{X}_i$ is a vector consisting of the levels of individual i on each of a set of characteristics. A more elaborate version of this model could be specified by, for example, assuming that certain characteristics act as "intervening variables" in explaining the relationship between other variables; for example, that marital status has a causal influence on things such as economic resources and frequency of social activities, which in turn have causal influences on subjective well-being, thereby explaining some or all of the relationship between marital status and well-being.

Possible Consequences of Model Misspecification

How much confidence can we place in estimates of the effects of one variable on another, such as the multiple regression coefficients that could be obtained as estimates of the β and γ parameters in expression (2)? There are several sources of possible error in such estimates. A familiar example, sampling variance, results from the use of a sample of cases to represent a population, and is relatively straightforward to estimate, allowing confidence intervals to be placed about point estimates. Other sources of error are more troublesome and less easily quantified. A major concern in the estimation of any model is the possibility that the model has been *misspecified*. If one or more of the causes of variability in the dependent variable have not been included in the causal model that is being estimated, and if those variables are related to the causal variables that *are* included in the model, then the magnitude of the model parameters may be biased either upward or downward depending on the pattern of covariances among the variables. In a real sense, this is an insoluble problem with observational (as opposed to experimental) data; it is impossible to prove that an important cause of the dependent variable has *not* been omitted from a model. The use of panel data does, however, allow us to make some headway if it is reasonable to make certain assumptions.

Consider the model specified by the following expression:

$$Y_i = \sum_{j=1}^{J} \beta_j D_{ij} + \underline{X}_i\underline{\gamma} + \underline{Z}_i\underline{\lambda} + \epsilon_i \quad . \tag{3}$$

This model is identical to that specified in expression (2) except for the inclusion of a set of M additional predictors, $\underline{Z} = \{Z_{i1}, Z_{i2}, \ldots, Z_{iM}\}$. If the $\underline{\lambda}$ coefficients are not all zero and the covariances of these Z variables with the marital status and transition variables are also not zero, then parameter estimates based on expression (2) would be biased. We can use expression (3) to estimate models that include such additional variables, either on the basis of a theory which hypothesizes causal effects of certain variables or on the basis of covariances observed in the sample data; however, such a strategy can only deal with Z variables that have been *measured* for the sample of cases being analyzed. If panel data are available, two strategies have been proposed to cope with the problem of *unmeasured* Z variables. We will consider both of these strategies.

Including Prior Level of the Dependent Variable as a Predictor of Current Level

The strategy that is probably most commonly used in the analysis of panel data is to include the dependent variable as measured at one or more previous times as a predictor of the current level. Too often, this procedure is adopted without considering the justification for it; let us instead take a critical look at the rationales which have been offered in support of this strategy.

One inducement for including past level of the dependent variable as a predictor of current level may be simply to increase the proportion of explained variance. More often than not, the strongest correlate of the current level of a variable is the past level of that same variable, and so the predictive power of a regression model is greatly enhanced by including past level as a predictor; so it might seem obvious that it *should* be so included. This is not a compelling rationale, however; within the present context of estimating causal models, the objective of regression analysis is to enhance our understanding of causal processes, not to maximize predictive power. An excellent predictor of a person's eye color today is that person's eye color yesterday, but no one would argue that yesterday's eye color in any sense "causes" today's eye color.

For some variables, a convincing argument can be made that prior level is a proximate determinant of current level. An example is the level of use of addictive drugs, such as nicotine. A person reports heavy cigarette use at one time at least in part *because* of heavy use at a prior time. While this may be true, it is nevertheless not very helpful to use prior smoking behavior as a predictor of current smoking behavior if our objective is not simply to predict who smokes and who does not, but to understand *why* certain people are more likely to *become* smokers than others. Whatever the dependent variable, it is difficult to make a convincing case that our understanding of its *basic* causes is enhanced by estimation of a model that includes as a predictor past level of that variable. This statement runs so counter to conventional practice, however, that it merits further discussion.

The assertion rests on the assumption that the past level of a variable is not a cause of current level. We cannot prove this as a general principle, but another example may be helpful. People who were satisfied with their lives last year are often satisfied this year as well, and we can postulate causal paths that could account for some of that stability. For example, those who are satisfied with their lives may be better able to establish and maintain good marriages, jobs, and so on, which in turn contribute to higher levels of satisfaction at a later time. Nevertheless, the basic causes of satisfaction are those other factors, such as good marriages and stable jobs and the personal characteristics which aid in getting into and staying in those situations. To estimate a causal model that includes past level of the dependent variable as a cause of present level may only serve to obscure the search for those more basic causes.

Another rationale that has been offered for including past levels on the dependent variable in the regression model for current level is a practical one: not that the past is itself a cause of the present, but that the past level is correlated with unmeasured causes of the present level. In terms of the model given by expression (3), the dependent variable at the earlier time is correlated with the omitted Z variables. The previous level (Y_1) is included, then, as a kind of instrumental variable for the Z variables. Y_1 is not a proper instrument, however, unless the differences between its values and those of the omitted Z variables can

be safely assumed to be *uncorrelated* with the predictors (i.e., the $\underline{X}_2$ variables) that *are* included in the regression. This rarely is a sensible assumption, since the reason for including the $\underline{X}_2$ variables in the regression model is precisely because they are thought to be related to the current level of the dependent variable (Y_2); this being the case, it is difficult to argue that, after controlling on the unmeasured Z variables, they would be unrelated to the level of the dependent variable at an earlier time (i.e., Y_1).

It still might be argued that, as a practical matter, it may be better to include the past level of the dependent variable in the prediction equation because it is better to include even an improper instrument for unmeasured variables than to ignore entirely the possibility of such unmeasured causes. Another approach is to ask whether there are alternative procedures for dealing with the possibility of misspecified models because of unmeasured Z variables. At least one such procedure has been proposed, and it is to a description of that procedure that we now turn.

Analysis of Change Scores

An alternative strategy that has been used with panel data to cope with the problem of possible unmeasured Z variables is to predict *change* rather than current level on the dependent variable. The rationale for this strategy is straightforward. The critical assumption is that the relevant Z variables do not change between data collections. This is most reasonable for characteristics which remain more or less fixed across the lifetime, or at least the adult lifetime, of an individual, as is often assumed about many personality characteristics. If expression (3) is written for two waves of data collection, say t=1 and t=2, and if the expression for time 1 is subtracted from the expression for time 2, the following difference equation is obtained:

$$\begin{aligned} \Delta Y_i &= Y_{i2} - Y_{i1} \\ &= \sum_{j=1}^{J} \beta_j (D_{ij2} - D_{ij1}) + (\underline{X}_{i2} - \underline{X}_{i1})\underline{\gamma} + (\epsilon_{i2} - \epsilon_{i1}) \ . \end{aligned} \tag{4}$$

One important feature to note about expression (4) is the disappearance of the Z variables. That is, conditional on the validity of the assumption that any omitted causal variables do

not vary across data collections, parameter estimates for the marital transition variables derived from the change score expression (4) are unbiased. The second important feature is that the predictor of key interest is marital *transition* — i.e., both the predictor and criterion dimensions are *change scores*.

The third important feature of expression (4) is that the "error" component — the term for the variance in the dependent variable that is not explained by the predictor variables — has changed. If this component is not stable (i.e., if ϵ_{i1} is unrelated to ϵ_{i2}), and if its variance is the same at times 1 and 2, then the variance of its change is twice that of its level at either time. This in turn would mean that the standard errors of estimates of regression coefficients would be larger if based on change scores than if based on level scores. It often is not realistic to assume that the error terms are not at all correlated over time, however. For example, respondents may differ in certain response tendencies — some may use the extreme answer categories more than others, some may have stronger tendencies to give socially desirable answers, and so on. To the extent that such response persist over time, they cancel out in the change scores, and in this respect are equivalent to omitted Z variables as discussed above.

There is another possible effect of such response tendencies, however: if a particular response tendency affects scores both on the dependent variable and on one or more of the predictor variables, biases are introduced into estimates of the regression coefficients, and such biases may be magnified if change scores rather than level scores are analyzed. Suppose, for example, that we were to find a strong correlation between changes in self-esteem and changes in life satisfaction. Before concluding that we had documented a genuine correlation between real changes, we should consider this alternative interpretation: neither self-esteem nor life satisfaction changed appreciably (especially if the changes were measured over a short interval), so when we subtracted Time 1 from Time 2 scores on both dimensions we were left with mostly error, and since the errors in the two dimensions covary (at any point in time) the observed correlation between change scores reflects only covarying errors. The implication is that the possibility of such correlated errors must be considered seriously. In the present examples, we did consider this possibility, and concluded that (a)

there were likely to be few errors in reporting marital status, living arrangements, parenthood, etc., and (b) any such errors were unlikely to be correlated strongly with errors in reporting life satisfaction or drug use.

Data Analysis

The analyses reported in this paper are taken from the Monitoring the Future study. The heart of this study is a series of nationwide questionnaire surveys of 16,000 to 17,000 high school seniors, conducted annually since 1975 by the Institute for Social Research at The University of Michigan. The data are collected through group-administered questionnaires with samples of students in each of about 130 public and private schools, selected in a manner that the participants are samples of the U.S. population of each senior class cohort. Another feature of the design is that it includes a longitudinal component. Follow-up questionnaires are mailed annually to a specially selected subset of each cohort. In order to monitor changes, these questionnaires contain many of the same questions as are used in the senior year, but they also include a number of new questions about post-high school experiences and behaviors. A primary focus of the Monitoring the Future study is on the use of, and attitudes about, licit and illicit drugs. In addition, there is a limited number of questions about the subjective quality of life. In this paper, we first estimate the parameters of causal models in which the dependent variables are two reports on the overall quality of life. We then repeat the exercise using as dependent variables two measures of drug use. Among the predictors included in these models, in addition to marital status, are status as a student, worker, or homemaker, and a set of demographic variables. The relevance of most of these variables to subjective well-being and to marital status is obvious. For example, marriage is often the occasion of a change in living arrangements, and it is important to try to separate the effects of these two types of transitions. Similarly, changes in work status are often associated with marital transitions, sometimes directly as with those who wait until their education is completed before considering marriage, other times more indirectly because of the greater importance of a job when a person has a family to support.

None of the models that we have estimated is at all complex or precisely defined with respect to the causal relationships among the variables included as predictors of subjective well-being. We suspect that some of these relationships are reciprocal rather than unidirectional. It is also likely that some of the predictors are better interpreted as intervening variables which partially explain the relationship between marital status and subjective well-being, while others may contribute to a spurious relationship. Our analyses treat the predictors as a parallel set of exogenous variables and thus take the relationships among them as given.

Time permits us to present only a highly condensed version of our findings, summarized in Table 1. Our procedure was to do multiple regression analyses in which the dependent variable was either a report of current level from one data collection, or change in such a report from one data collection to the next. In the first set of regressions, summarized in the first column of Table 1, marital status (married vs. unmarried) was always included as a predictor. For example, in the first row this is the only predictor, and we see that married persons are about a quarter of a standard deviation higher than unmarried persons in their reports of satisfaction and happiness. The estimates obtained when prior level of the dependent variable is included as a predictor are shown in the second columns of these tables. Finally, the estimates based on the change scores from time 1 to time 2 (for both the predictors and the dependent variables) are shown in the last column of Table 1. The remaining rows of Table 1 are the average of estimates based on each of these three types of model when other predictors are added to the regression analyses.

We note first that the estimated bivariate effects of marital status on subjective well-being as derived from change scores are considerably smaller than the estimates derived from static scores. The overestimation (as we would view it) of the static score coefficients is markedly reduced by introducing prior level of the dependent variable as a predictor of current level. These estimates remain larger than those based on change scores, but not by much. In this respect, the introduction of the prior level of the dependent variable as a predictor of current level is an improvement in the model.

Table 1
Comparison of Estimated Effects of Marital Status on Levels of Life Satisfaction and Happiness Based on Analyses of Change and Static Scores (Monitoring the Future Panel Data)

Variables Controlled	Dependent Variable		
	Static Scores (Y2)	Y2, Control on Y1	Change Scores (Y2 – Y1)
Nothing	.247 (.055)	.176 (.053)	.146 (.071)
Living arrangements	.184 (.058)	.127 (.056)	.141 (.075)
Whether parent	.327 (.062)	.245 (.059)	.155 (.075)
Work/student status	.350 (.059)	.259 (.057)	.145 (.072)
Complete set	.298 (.068)	.228 (.066)	.189 (.079)

NOTES: Each of the entries is the average of four partially standardized regression coefficients, predicting life satisfaction and happiness separately for men and women. The entries in the first column are based on analyses in which the dependent and predictor variables are all their levels at time 2. Those in the second column are the same as the first, except that level of the dependent variable at time 1 is included as a predictor of level at time 2. Those in the third column are based on analyses in which the dependent variable is change from time 1 to time 2.

In other respects, this procedure is less successful in reducing bias in estimates of marital status effects. Note in particular that estimates based on change scores are not affected much at all by adding living arrangements, parenthood, or work and student status to the regression model. This is in contrast to the substantial impact of including these variables on the estimates based on static scores. Adding the prior level of the dependent variable as well does not improve this situation much; the differences between entries in the second column of Table 1 are almost as great as the differences between entries in the first column. We interpret this variation to the omission of relevant variables from the static score models. If some of these omitted variables did not change between time 1 and time 2, as appears to be the case, then their omission from the change score models is irrelevant.

Parallel comparisons of the effects of marital status on drug use as estimated from level and change scores are shown in Table 2. The general patterns are the same as those with respect to subjective well-being shown in Table 1. The entries in the second and third column of Table 2 are generally more similar to one another than are the entries in those columns of Table 1, indicating less of a divergence between the two estimation procedures (change scores vs. including time 1 scores as a predictor of time 2 scores). We attribute this closer agreement between the methods to the higher stability in reported levels of alcohol and marijuana than is true for reports of subjective well-being.

The use of change scores offers a clear advantage over the use of static scores by reducing the potential for misspecified models. There is a price, however: in general, the standard errors of estimates based on change scores are greater than those based on static scores. The conventional wisdom tells us that this increase is likely to be large and that for this reason the use of change scores to estimate static models is to be eschewed. The conventional wisdom is wrong, however. For reasonably large sample sizes, and for a wide range of stabilities of the true values and measurement errors in the predictor variables, the ratio of the sampling errors for estimates based on change scores to those based on static scores is *not* excessively large. We base this assertion both on the analyses we have summarized here and on mathematical considerations developed elsewhere (Rodgers and Bachman, 1985).

Table 2
Comparison of Estimated Effects of Marital Status on Frequency of Use of Alcohol and Marijuana Based on Analyses of Change and Static Scores (Monitoring the Future Panel Data)

Variables Controlled	Dependent Variable		
	Static Scores (Y2)	Y2, Control on Y1	Change Scores (Y2 – Y1)
Nothing	–.301 (.051)	–.186 (.040)	–.180 (.049)
Living arrangements	–.379 (.053)	–.232 (.042)	–.220 (.052)
Whether parent	–.305 (.057)	–.185 (.045)	–.167 (.051)
Work/student status	–.355 (.054)	–.205 (.043)	–.174 (.050)
Complete set	–.405 (.061)	–.245 (.050)	–.189 (.054)

NOTES: See notes to Table 1. Each of the entries is the average of four partially standardized regression coefficients, predicting heavy drinking and marijuana use separately for men and women.

Dynamic Models

Another strength of panel data as compared to cross-sectional data is the increased opportunity they offer for estimation of dynamic causal models. We do not have time to discuss such models today, beyond a brief description and a word of explanation of the importance of panel data for their estimation. Most of the interpretations of causal relationships that we have enumerated up to this point have been basically static in nature: for example, that one marital status is more satisfying than another, or that some kinds of people are more likely than others to give socially desirable answers to interview questions. Other types of explanations are more dynamic, including one that we have already mentioned: some people may be more likely to marry at relatively young ages than others, and this could result in a spurious relationship between marital status and life satisfaction. Causal hypotheses of this type are commonly estimated through use of retrospective data (event histories), but panel data offer definite advantages by establishing clearer evidence concerning the timing of events.[1]

For examining other types of dynamic models, panel data may be essential. If the model involves subjective phenomena, such as attitudes or evaluations, or events the occurrence or timing of which are soon forgotten, then retrospective reports may easily be distorted by subsequent events. For example, it would be foolhardy to use retrospective data to test the hypothesis that dissatisfaction with marriage increases the probability of divorce. Even if a strong relationship were found between level of marital satisfaction, as reported retrospectively for some time in the past, and subsequent probability of divorce, an obvious alternative explanation would be that respondents' memories of their feelings about a marriage (or their reports of those feelings) may have been influenced by the subsequent disposition of that marriage. Panel data, on the other hand, would not suffer from this limitation. The relationship between self-reported marital satisfaction on one occasion and subsequent probability of divorce, as measured on later occasions, would offer solid evidence

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[1]Techniques for estimation of dynamic models are reviewed in several recent articles and books, most notably Tuma and Hannan (1984). Other references include Allison, 1984; Coleman, 1981; and Kessler and Greenberg, 1981.

for a causal relationship. This is not to say that there would not be other competing explanations to explore, but only that the obvious competing explanation of faulty recall would not be at issue.

The distinction between static and dynamic models is probably largely artificial, an accident imposed by the fact that much of social science data is cross-sectional with only crude approximations of temporal variation. As panel data become more widely available, and as techniques for estimation of explicitly dynamic models become more widely known, the distinction may become less important. Nevertheless, we still find it useful to distinguish between causal explanations that focus on the *states* that individuals are in at a particular time and those that focus on the *process* by which individuals come to be in those states, including factors that influence the probability of changing from one discrete state to another and those that influence the rate at which a continuous variable is changing. Returning to the example of the relationship between marital status and satisfaction with life, we have already considered the first type of explanation: the married state may be intrinsically more satisfying for most people than any other marital status. A possible dynamic explanation for the observed relationship is that the transition from the single to the married status produces a positive gradient in satisfaction for most people. In other words, perhaps it is not that marriage as a state is more satisfying than any other status, but rather that the marriage *event* produces a large, though possibly transient, surge in satisfaction.

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